

PREDICTION OF A COMMUNICATION SATELLITE DRIVEN BY WHITE NOISE SEQUENCE
(A DETERMINISTIC APPROACH TO LINEAR SIGNAL FILTERING)

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ABSTRACT

This paper presents a qualitative evaluation of a communication satellite driven by a white noise sequence, and proposes a filtering solution to predict the dynamics of the satellite. The prediction of the position and velocity of the communication satellite though being perturbed by the effect of solar array, gravity waves and drag resistance, was achieved using a least square algorithm based filter to determine an unbiased estimate. The dynamics of the satellite assumed linear, were examined from three broad classifications viz a viz: Parametric estimation (Least Mean Square method), Noise in communication system and the Kalman Filter. The significant practical benefits of using the MATLAB program for the Kalman filter blockset in the simulations were established.

KEYWORDS: Communication Satellite, White Noise, Least Mean Square, Unbiased estimates, Kalman filter

INTRODUCTION

Filtering is desirable in many situations in engineering and embedded systems. Radio communication signals are often corrupted or heavily correlated with noise. A good filtering algorithm can remove the noise from electromagnetic signals while retaining the useful information (Simon, 2001). For many space applications involving data communication, a large number of satellites have been launched into the earth orbit, for effectiveness in their operation, the attitude must be observable and the dynamics predictable. It is possible to obtain a time history of the attitude of a communication satellite by suitable instrumentation and telemetry (Ekejiuba, 1986). A near-earth satellite, for example, orbiting in the attitude range of 150 km to 450 km encounters small but non-negligible aerodynamic forces due essentially to the characterization of drag resistance, gravity waves in stably stratified atmosphere especially affects free and forced rotation of astronomical satellites (Sohn, 1995). The influence of major environmental forces on the attitude response of gravity gradient satellites using both analytical and numerical techniques presents a problem of major interest to the telecommunication engineer. This is a game theory approach; Nature tries to maximize the estimation error, the engineer tries to minimize the error (Simon, 2008). This work models the dynamics of a communication satellite driven by a white noise sequence, and proposes a finite-time signal filtering solution using the Kalman filter, in which state estimation was addressed. Theoretically, the Kalman filter is an estimator for what is called the linear-quadratic problem, which is the problem of estimating the instantaneous "state" of a linear dynamic system perturbed by white noise—by using measurements linearly related to the state but corrupted by white noise. The resulting estimator is statistically optimal with respect to any quadratic function of estimation error. Practically, the Kalman filter is one of the greatest discoveries in the history of statistical estimation theory and possibly the greatest discovery in the twentieth century. It has enabled humankind to do many things that could not have been done without it, and it has become as indispensable as silicon in the makeup of many electronic systems. Its most immediate applications have been for the control of complex dynamic systems such as continuous manufacturing processes (Grewal and Andrews, 2008). The Kalman filter provides an efficient computational means to estimate the state of a process, in a way that minimizes the mean of the squared error. It supports estimations of past, present, and even future states, and it can do so even when the precise nature of the modeled system is unknown. Our approach determines the best estimate: the measured values of the input and output of the system are required, where by the measured error covariance and the estimated error covariance must be approximately same or unbiased.

Statement of the Problem

[CGWIC 2007]The NigComSat-1 was the first African geosynchronous communication satellite, when it was launched into orbit, aboard a Chinese Long March 3B carrier rocket, from the Xichang Satellite Launch Centre in China. The satellite, which is the third Nigerian satellite to be placed into orbit, was launched into a geosynchronous transfer orbit and subsequently it was successfully inserted into a geosynchronous orbit, positioned at 42.5°E on 13 May 2007. It had a launch mass of 5,150 kg, and had an expected service life of 15 year. The satellite, designed to operate in Africa, parts of the Middle East and southern Europe, is to serve mobile phone users, facilitate internet performance in remote regions and improve overall

telecommunications. The spacecraft was operated by NigComSat and the Nigerian Space Agency, NASRDA, it is been monitored and tracked by a ground station built in Nigeria's capital Abuja. On 10 November 2008 (0900 GMT), the satellite was reportedly switched off for analysis and to avoid a possible collision with other satellites. According to Nigerian Communications Satellite Limited, it was put into "emergency mode operation in order to effect mitigation and repairs" (AFP, 2008). On November 11, 2008, NigComSat-1 failed in orbit after running out of power due to an anomaly in its solar array. The need to predict and achieve an unbiased estimate of the actual path and position of a communication satellite is of great concern, hence this study.

Significance of Study

This study will no doubt be of immense benefit in the tracking a communication satellite as it helps to predict the present, and future position of the satellite at any required time. Since received signals are heavily correlated with noise, filtering is desirable in other to control a dynamic system, for this application, it is not always possible or desirable to measure every variable that you want to control, Kalman filter is used for predicting the likely future courses of dynamic systems that people are not likely to control, it provides a means for inferring the missing information from indirect and noisy measurements also giving the best estimate of the signal output thereby improving Signal to Noise ratio and Efficiency which are the desires of the telecommunication Engineer.

The State Estimation Problem

The procedure employed in least squares estimation of a process is usually carried out for a sequence of different order process and noise models until the best and simplest possible model is obtained. The more general estimation problem can be formulated on the basis of maximum likelihood and Bayesian techniques (Athans, 1971; Kalman, 1960) using statistical information in terms of joint probability distribution functions. However, for the linear dynamic system with additive, zero-mean white Gaussian measurement noise defined in terms of mean values and variances, which will be appropriate for many practical problems, the least-squares solution formulated as a deterministic problem with appropriate weighting leads to the maximum likelihood estimate. (Oyediran, 2010) Computation of the optimal estimates should consequently rely on convergence of the iteration employed; this is accomplished through sequential filtration of the estimate.

Here, we consider a time-series model of the form

$$x(j) + \sum_{i=1}^m \alpha_i x(j-i) = \sum_{i=0}^m b_i u(j-i) \quad (1)$$

The partial fraction expansion required for obtaining a time solution to (1) is defined for distinct roots using the method of residues, as

$$Y(s) = \sum_{v=1}^k \sum_{k=1}^{m_v} \frac{\alpha_{vk}}{(s - \sigma_v)^k} \quad (2)$$

where $\alpha_1 \dots \alpha_k$ are the poles of the function $Y(s)$ with multiplicities $m_1 \dots m_k$.

The inversion integral was then written in the form

$$y(t) = \frac{1}{2\pi i} \int_{\sigma-i\infty}^{\sigma+i\infty} Y(s) e^{st} ds = \sum_{v=1}^k \sum_{k=1}^{m_v} \frac{C_{vk}}{(k-1)!} t^{k-1} e^{\sigma_v t}, \quad t > 0 \quad (3)$$

so that the function $Y(s)$ with contaminated noise becomes

$$Y(s) = \left[\sum_{i=1}^n \frac{\beta_i}{s + \alpha_i} \right] U(s) + \text{white noise} \quad (4)$$

where α_i, β_i are the parameters of the system, and n is the order of the system

Using the shift operator z^{-1} defined by $z^{-1}x(j) = x(j-1)$, equation (1) becomes

$$y(j) = \frac{B(z^{-1})}{A(z^{-1})} u(k) + \lambda \frac{c(z^{-1})}{A(z^{-1})} e(k), \quad k = 1, \dots, N \quad (5)$$

where $y(k)$ is the observed output signal, $u(k)$ is the applied input signal, N is the number of samples and $e(t)$ is the noise sequence. The polynomial operators A , B , and C are defined as follows

$$\begin{aligned} A(z^{-1}) &= 1 + \sum_{i=1}^{NA} \alpha'_i z^{-i} \\ B(z^{-1}) &= \sum_{i=1}^{NB} b'_i z^{-i} \\ C(z^{-1}) &= 1 + \sum_{i=1}^{NC} c'_i z^{-i} \end{aligned} \quad (6)$$

If the continuous model in (4) is discretized we shall obtain a discrete time model of the form

$$y(k) = \sum_{i=1}^n \frac{b_i z^{-1}}{1 + a_i z^{-1}} u(k) + \lambda e(k) \quad (7)$$

where the parameter set a, b is related to the parameter set α, β via the relation

$$\begin{aligned} a_i &= -\exp(-\alpha_i T) \\ \text{and } b_i &= \frac{\beta_i}{\alpha_i} (1 - \exp(-\alpha_i T)) \end{aligned} \quad (8)$$

where T is the sampling interval in seconds. The infinite noise of the discrete observations due to aliasing that may result from the above discretization process is negligible. This is justified if $u(k)$ and $e(s)$ are independent of all k and s . This is a reasonable assumption as long as the identification is performed for data acquired from experiments, where $u(k)$ is a priori known sequence. In some practical situations, this assumption is often violated when operating records are used because in such a case the input may depend on the output through feedback.

The canonical model in (5) was made equivalent to the discrete-time model of (7) by satisfying the conditions

$$\begin{aligned} \text{(i)} \quad c'_i &= a'_i \\ \text{(ii)} \quad \frac{B(z^{-1})}{A(z^{-1})} &= \sum_{i=1}^n \frac{b_i z^{-1}}{1 + a_i z^{-1}} \end{aligned} \quad (9)$$

The statistical method of maximum likelihood was employed to optimize the probability of obtaining the expected result. Consequently, a loss function $V(\theta)$ was defined as follows

$$V(\theta) = \frac{1}{2} \sum_{k=1}^N \varepsilon^2(k) \quad (10)$$

which will be minimized with respect to the system parameter set $\theta = [a', b']$. The residues were defined by

$$\varepsilon(k) = y(k) - \frac{B(z^{-1})}{A(z^{-1})} u(k) \quad (11)$$

so that the values of the parameter set a' and b' that make $V(\theta)$ in (10) minimum will be the estimates of the parameters of the system. The approach considered is one of finding the coefficients of the prediction model

$$\hat{y}\left(\frac{k}{k-1}\right) = \frac{B(z^{-1})}{C(z^{-1})} u(k) + \frac{C(z^{-1}) - A(z^{-1})}{c(z^{-1})} y(k) \quad (12)$$

so that the mean square prediction error

$$V(\theta) = \sum_{k=1}^N y(k) - \hat{y}\left(\frac{k}{k-1}\right)^2 = \sum_{k=1}^N \varepsilon^2(k) \quad (13)$$

is as small as possible. By doing so the assumption of Gaussian distribution of the noise sequence $\varepsilon(k)$ may be relaxed. In the model given in (7), the residues were obtained as

$$\varepsilon(k) = y(k) - \left(\sum_{i=1}^n \frac{b_i z^{-1}}{1 + a_i z^{-1}} \right) u(t) \quad (14)$$

For system order greater than n , $\varepsilon(k)$ as given in (14) becomes computationally difficult and highly nonlinear, whereas in the model of (7), the residues given by (11) may be computed quite easily for any given system order. Since the two models are equivalent via the transformations defined in (9), we are free to use any of them. Thus the form of residues given in (11) is recommended and used in this study for parameter estimation, and application of a filter for signal noise attenuation becomes evident.

Measurement Noise Filtration

The relationship between Information, Bandwidth and Noise Rate

$$R = 2B \log_2(n) \text{ b/s} \quad (15)$$

Signal to Noise Ratio

$$SNR = 10 \log_{10}(S/N) \text{ dB} \quad (16)$$

(Jianfeng, 2007) There is a theoretical maximum to the rate at which information passes error free over a channel. This maximum is called the *channel capacity*, C . The famous Hartley-Shannon Law states that the channel capacity, C is given by

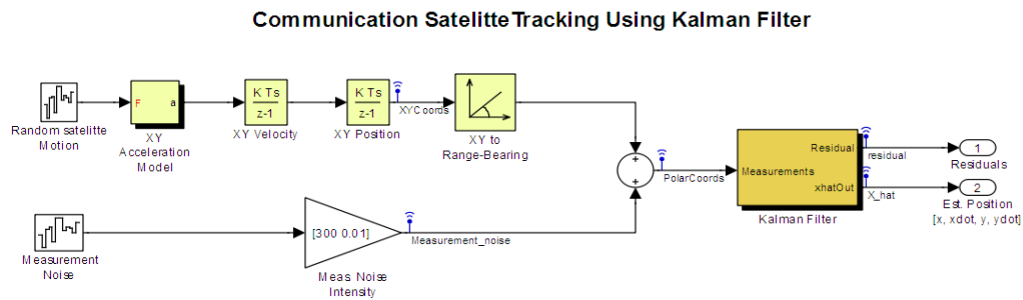
$$C = B \log_2(1 + (S/N)) \text{ b/s} \quad (17)$$

For example, a 10kHz channel operating at a SNR of 15dB has a theoretical maximum information rate of $10000 \log_2(31.623) = 49828 \text{ b/s}$.

METHODS

Figure 1 the block design, it shows a model that has three main functions. It generates the position, velocity, and acceleration in polar (range-bearing) coordinates; it adds measurement noise to simulate inaccurate readings by the sensor; and it uses a Kalman filter to estimate position and velocity from the noisy measurements.

a



b

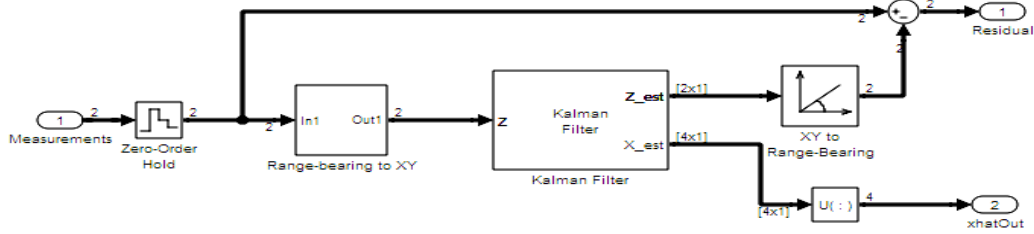


Figure 1(a and b): Block diagram of the study design {Kalman filter tracking of the ComSat}

The model is designed with the function kalman, having the following input data below

1. Kalman Filter
 1. Range-bearing to XY
2. XY Acceleration Model

Table 1: Showing Simulation Parameter

Simulation Parameter	Value
Solver	FixedStepDiscrete
RelTol	1e-3
AbsTol	1e-6
Refine	1
MaxStep	0.1
MaxOrder	5
ZeroCross	On

Table 2: Band-Limited White Noise. Block Properties

Name	Cov	Ts	Seed
Measurement Noise	[2 2]	0.1	[52341 62341]
Random satellite Motion	[0.001 .001]	0.1	[58413 74925]

Table 3: Gain Block Properties

Name	Gain	Multiplication	Param Min	Param Max	Param Data Type Str	Out Min	Out Max	Out Data Type Str
Meas. Noise Intensity	[300 0.01]	Element-wise(K.*u)	[]	[]	Inherit: Same as input	[]	[]	Inherit: Same as input

Table 4: Showing Block Types and Block Names

BlockType	Count	Block Names
SubSystem	2	Kalman Filter, XY Acceleration Model
Outport	2	<u>Est. Position [x, xdot, y, ydot], Residuals</u>
DiscreteIntegrator	2	<u>XY Position, XY Velocity</u>
Band-Limited White Noise. (m)	2	Measurement Noise, Random satellite Motion
xy2rtheta (m)	1	XY to Range-Bearing
Sum	1	<u>Sum</u>
Gain	1	<u>Meas. Noise Intensity</u>

Table 5: Model Variables Showing Initial Value

Variable Name	Parent Blocks	Calling string	Value
Speed	<u>XY Position</u>	[0,Speed]	400
	<u>XY Velocity</u>	[0,Speed]	

First we specify the satellite model with the process noise.

Consider the discrete linear system with additive Gaussian noise w_k on the input u_k data.

$$x_{k+1} = Ax_k + Bu_k + w_k \quad (18)$$

$$y_k = Cx_k \quad (19)$$

We want to use the available measurements y to estimate the state of the system x . We know how the system behaves according to the state equation, and we have measurements of the position, so how can we determine the best estimate of the state x ? We want an estimator that gives an accurate estimate of the true state even though we cannot directly measure it. For this system w is the process noise and z is the measurement noise. We have to assume that the average value of w is zero and the average value of z is zero. We have to further assume that no correlation exists between w and z , having in mind the properties of a white noise. That is, at any time k , w_k , and z_k are independent random signal variables. Then the noise covariance matrices S_w and S_z are defined as

Process noise covariance

$$S_w = E(w_k w_k^T) \quad (20)$$

Measurement noise covariance

$$S_z = E(z_k z_k^T) \quad (21)$$

where w^T and z^T indicate the transpose of the w and z random noise vectors, and $E(\cdot)$ means the expected value. There are many alternative but equivalent ways to express the Kalman filter equations. One of the formulations is given as follows:

$$K_k = AP_k C^T (CP_k C^T + S_z)^{-1} \quad (22)$$

$$\hat{x}_{k+1} = (A\hat{x}_k + Bu_k) + K_k(y_{k+1} - C\hat{x}_k) \quad (23)$$

$$P_{k+1} = AP_k A^T + S_w - AP_k C^T S_z^{-1} CP_k A^T \quad (24)$$

The K matrix is called the Kalman gain, and the P matrix is called the estimation error covariance. The aim is to estimates the output y_k given the inputs u_k and the noisy output measurements

$$y_k = Cx_k + z_k$$

where z_k is some Gaussian white noise.

The first task during the measurement update is to compute the Kalman gain, The next step is to actually measure the process to obtain y_k , and then to generate an *a posteriori* state estimate by incorporating the measurement. The final step is to obtain an *a posteriori* error covariance estimate.

After each time and measurement update pair, the process is repeated with the previous *a posteriori* estimates used to project or predict the new *a priori* estimates. This recursive nature is one of the very appealing features of the Kalman filter—it makes practical implementations much more feasible than an implementation of a

Wiener filter which is designed to operate on *all* of the data *directly* for each estimate. The Kalman filter instead recursively conditions the current estimate on all of the past measurements.(Welch and Bishop 2006)
The equations of the steady-state Kalman filter for this problem are given as follows.

Measurement Update

$$x_{(k)} = x_{(k-1)} + P_k(y_k - Cx_{(k-1)})$$

Time Update

$$\hat{x}_{k+1} = (A\hat{x}_k + Bu_k) + K_k(y_{k+1} - C\hat{x}_k)$$

In these equations:

- $x_{(k-1)}$ is the estimate of $x_{(k)}$ given past measurements up to y_{k-1}
- $x_{(k)}$ is the updated estimate based on the last measurement

Given the current estimate, $x_{(k)}$ the time update predicts the state value at the next sample $k+1$ (one-step-ahead predictor). The measurement update then adjusts this prediction based on the new measurement y_{k+1} . P is the correction term is a function of the *innovation*, that is, the discrepancy between the measured and predicted values of y_{k+1} . The innovation gain K_k (Kalman gain) is chosen to minimize the steady-state covariance of the estimation error given the noise covariances. This filter generates an optimal estimate of y_e .

Note that the filter state is $x_{(k-1)}$

Example: Given that

A =

$$\begin{bmatrix} 3.1270 & -0.9430 & 339 \\ 1.0000 & 0 & 0 \\ 0 & 1.0000 & 0 \end{bmatrix}$$

B =

$$\begin{bmatrix} -0.7660 \\ 0.8190 \\ 0.7330 \end{bmatrix}$$

C =

$$\begin{bmatrix} 1 & 0 & 0 \end{bmatrix}$$

D = 0

Now we can construct a state-space model of the block diagram with the functions parallel and feedback. We build a complete mathematical model with u, w and as inputs y and y_v (measurements) as outputs.

$a = A;$

$b = [B \ B \ 0*B];$

$c = [C;C];$

$d = [0 \ 0 \ 0; 0 \ 0 \ 1];$

$P = ss(a,b,c,d,-1,'inputname',\{'u' \ 'w' \ 'v'\},... \\ 'outputname',\{'y' \ 'y_v'\});$

To simulate the filter behavior we generate a sinusoidal input u and process and measurement noise vectors w and v .

$t = [0:100]$ time is from 0 to 100secs, $u = \sin(t/15)$, $Sw = 3.2$, $Sz = 1$, $n = \text{length}(t) = 101$

$\text{randn}('seed',0)$, $w = \sqrt{Sw} * \text{randn}(n,1)$, $v = \sqrt{Sz} * \text{randn}(n,1)$

we simulate to get

$[out,x] = \text{lsim}(\text{SimModel},[w,v,u]);$

$y = out(:,1);$ true response, $y_e = out(:,2);$ filtered response, $y_v = y + v;$ measured response

The Kalman Gain $K =$

1.0e+005 *
 4.5195 0.0000 0.0065
 0.0000 0.0000 0.0000
 0.0065 0.0000 0.0000

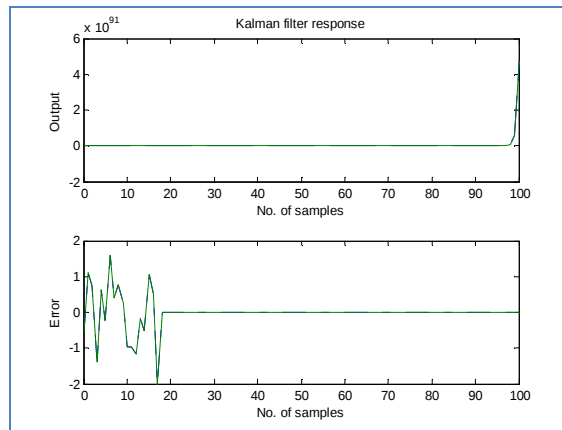


Figure2: Kalman Filter Response (output and error)

Measured Error is

$\text{MeasErr} = y - y_v;$

Measured Error Covariance is given by

$\text{MeasErrCov} = \text{sum}(\text{MeasErr} * \text{MeasErr}) / \text{length}(\text{MeasErr});$

Estimated Error is

$\text{EstErr} = y - y_e;$

Estimated Error Covariance is given by

$\text{EstErrCov} = \text{sum}(\text{EstErr} * \text{EstErr}) / \text{length}(\text{EstErr});$

Measured Error Covariance is = 0.1657

Estimated Error Covariance is = 0.1657

Note since the measured error covariance and the estimated error covariance have same value we are sure of determining an unbiased estimate of the position of the Communication satellite.

Simulation of Position of the Communication Satellite

Initial Velocity Mismatch

The Kalman Filter block works best when it has an accurate estimate of the satellite position and velocity, but if given time it can compensate for a bad initial estimate.

To see this,

Given Initial condition for estimated state parameter in the Kalman Filter as follows,

Initial Satellite E-W estimate Position, with initial velocity of 400 in the Y direction,

time $t = [0 \text{ to } 100]$ seconds at intervals of 10s, we have the result in figure 3 below:

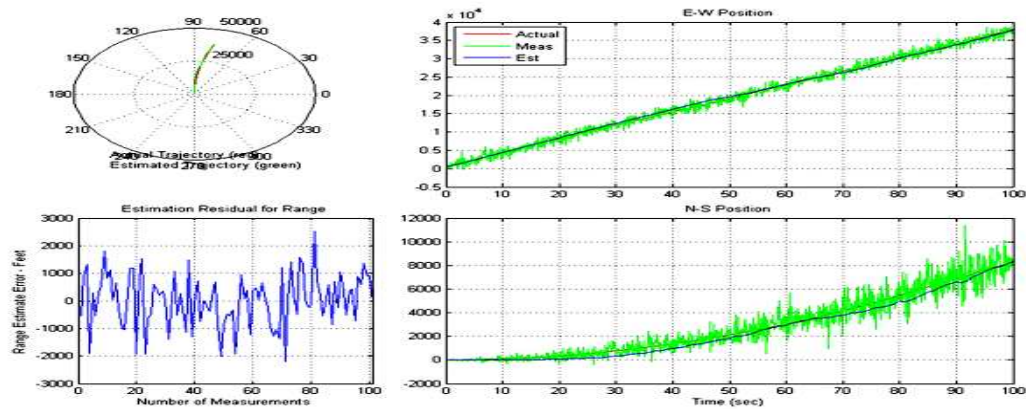


Figure 3 Initial Satellite E-W estimate Position, with initial velocity of 400 in the Y direction

RESULTS AND ANALYSIS

Estimation of the position and velocity is performed by the 'Kalman Filter' subsystem. This subsystem samples the noisy measurements, converts them to rectangular coordinates, and sends them as input to the Signal Processing block set, Figure 1b

The Kalman Filter block produces two outputs in this application.

- An estimate of the actual position. This output is converted back to polar coordinates so it can be compared with the measurement to produce a residual, or error (the difference between the estimate and the measurement). The Kalman Filter block smooths the measured position data to produce its estimate of the actual position.
- The second output from the Kalman Filter block is the estimate of the state of the satellite. In this case, the state is comprised of four numbers that represent position and velocity in the X and Y coordinates.

Changing the estimate from 400 to 100 and running the model again, we have

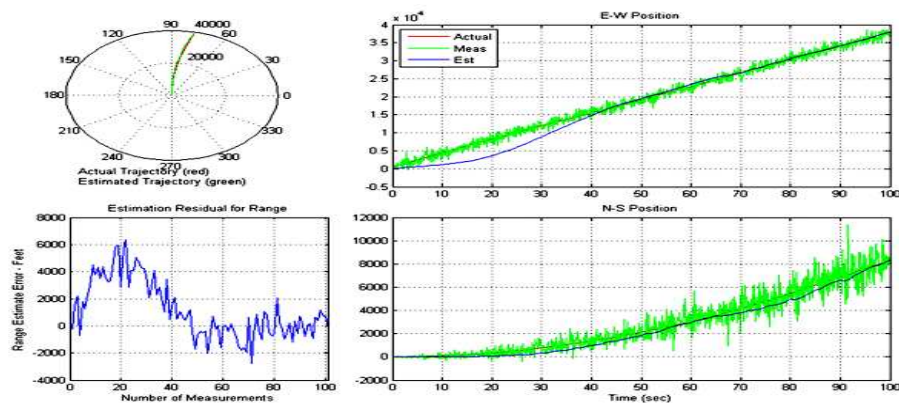


Figure 4: Showing Velocity in Y direction=100

It is observed that the range residual is much greater and the 'E-W Position' estimate is inaccurate at first. Gradually, the residual becomes smaller and the position becomes more accurate as more measurements are gathered.

Simulation by increasing the Measurement Noise Estimate

In the present model, the noise added to the range estimate is rather small compared to the ultimate range. The maximum magnitude of the noise is 300 ft, compared to a maximum range of 40,000 ft. Increasing the magnitude of the range noise to a larger value, for example, 5 times this amount or 1500 ft. by changing the first component of the Gain parameter in the 'Meas. Noise Intensity' Gain block.

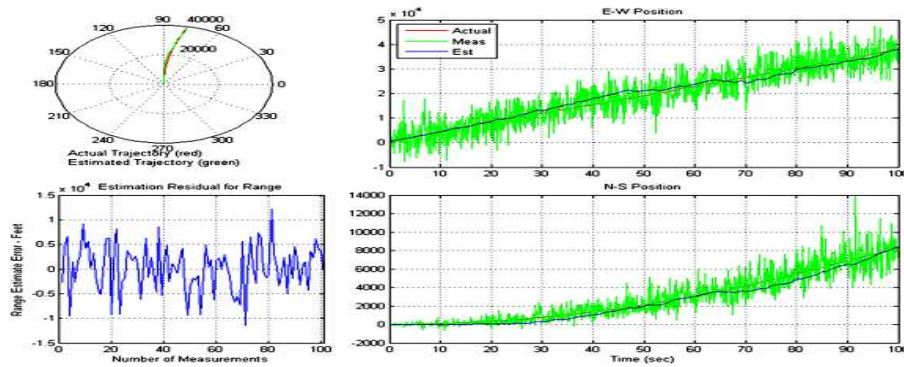


Figure 5: Poor Prediction

We observe that the blue lines representing the estimated positions have moved farther from the red lines representing the actual positions, and the curves have become much more 'bumpy' and 'jagged'. We can partially compensate for the inaccuracy by giving the Kalman Filter block a better estimate of the measurement noise. Setting the Measurement noise covariance parameter of the Kalman Filter block to 1500 and running the model again.

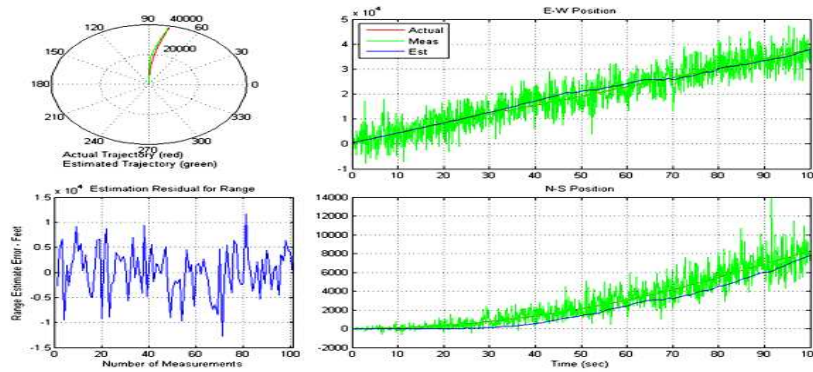


Figure 6 Showing Unbiased Estimate

ANALYSIS AND DISCUSSION

- From Figure 2 the covariance plot, one can see that the output covariance did indeed reach a steady state in about five samples., the Covariances arrived at the same value, being the same, that means that estimated output of our kalman filter is unbiased, thereby achieving the aim of the study.
- From figure 5, It is noted that when the measurement noise estimate is better, the E-W and N-S position estimate curves become smoother. This is the expected behavior.

CONCLUSION AND RECOMMENDATION

Conclusion: For communication satellites launched in the orbit, the intricacy of predicting its position in the orbit is high due to the effect of gravity waves, drag resistance, solar arrays etc, which give rise to erroneous range detection of the space craft. The kalman filter has profer a solution to the mentioned problems, it is important to state here that it not only works well in practice, but it is theoretically attractive because it can be shown that of all possible filters, it is the one that minimizes the variance of the estimation error.

RECOMMENDATION

It is recommended that the Kalman filter is being used to filter noise in order to track or predict linear systems. Many physical processes, can be approximated as linear systems and can be predicted e.g. vehicle driving along a road, a motor shaft driven by winding currents, or a sinusoidal radio-frequency carrier signal.

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